Application of Geospatial Technologies to Determine Imperviousness in Peri-Urban Areas

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Abstract

In homogeneous (either urban or rural) areas it is generally possible to get a better land use classification due to the distinct spectral reflectance values between different types of land use. But in peri-urban areas due to dual influence of rural and urban land covers, it is difficult to find out the land uses as identical reflectance values can correspond to different type of land uses serving different types of functions. Hence the quality of classification is poorer both in terms of the number of individual classes that can be identified and the accuracy with which these classes can be determined. To minimize this type of misclassification in land use classification, additional tools like GIS derived data has been used in the current study and hence a comparison is presented between the imperviousness obtained by two methodologies. The study can be useful for accessing the accuracy of runoff prediction by employing the imperviousness obtained above in the hydrologic model.

Keywords

Imperviousness; Peri-Urban Area; Geospatial Techniques

Introduction

Urbanization mainly refers to the increase in impervious (concrete) area that blocks the free flow of water into the down soil [2, 11, 14] leading to increase in surface runoff. Hence information regarding imperviousness is very much essential for urban hydrology and watershed management. Many earlier reported studies [1, 7, 8] have emphasized the effect of imperviousness on changing hydrological characteristics of a watershed. Most of these studies employ the geospatial techniques to deal with the spatial component of the urban watersheds. The remote sensing technologies mainly used were the classification of satellite imageries of low [12] and high spatial resolution. Spatial resolution, spectral resolution and classifier algorithms are the most important parameters that affect the image classification process the most [3, 5]. In homogeneous (either urban or rural) areas it is generally possible to get a better land use classification due to the distinct spectral reflectance values between different types of land use. But in peri-urban areas due to dual influence of rural and urban land covers, it is difficult to find out the land uses as identical reflectance values can correspond to different type of land uses serving different types of functions. Hence the quality of classification is poorer both in terms of the number of individual classes that can be identified and the accuracy with which these classes can be determined. To minimize this type of misclassification in land use classification, additional tools like GIS derived data has been used in the current study and hence a comparison is presented between the imperviousness obtained by two methodologies.

Study Area

The study area, Guwahati as depicted in Fig. 1 is a part of Kamrup District in Assam (North East India), and is situated between 26^0 4′ 45″ and 26^0 13′ 25″ North Latitude and between 91^0 34′ 25″ and 91^0 52′ 00″ East Longitude. Located on the Bank of River Brahmaputra, it is the largest commercial, industrial and educational centre of the north east India and a rapidly expanding urban city. The city is situated on an undulating plane of varying altitude of 47.0m to 55.5m above Mean Sea Level (MSL). The southern and eastern sides of the city are surrounded by hillocks. Apart from the hilly tracts, swampy/ marshy lands and water bodies cover a considerable portion of the city. The methodology used in this study is demonstrated with respect to one of its watersheds i.e *Silsako* watershed. To best capture the spatial variability of the catchment parameters, Silsako watershed has been further segregated into 22 sub-watersheds in ArcGIS 9.3.1 platform.

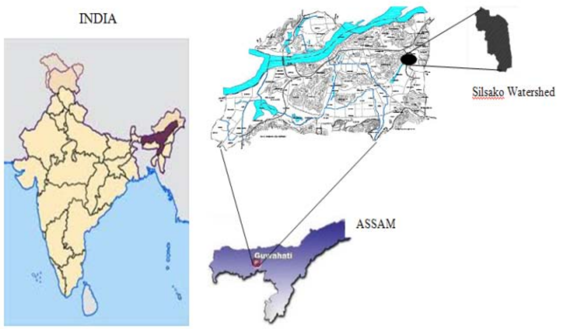


FIG. 1 LOCATION OF *SILSAKO* WATERSHED OF GUWAHATI CITY

Methodology

A combination of remote sensing and GIS has been used to estimate imperviousness [9], in the current study. The imperviousness is obtained from the LISS4 (5m spatial resolution) imagery. A False Colour Composite (FCC) of the image was formed (NIR band 0.76μm as Red, red band of 0.62 μm as Green and green band of 0.52 μm as Blue) as an initial step to the image analysis using image processing software ENVI-4.6 (Environment for Visualization of Images). The FCC image was then classified into different classes to obtain the classified images. Supervised Maximum Likelihood classifier (algorithm) has been applied as it gives the highest overall accuracy [13] as compared to other classification schemes. The imagery has been classified into eight basic classes namely building rooftops, asphalt/concrete (collectively called built-up area), water body, forest, scrub land, agricultural land, swampy/ marshy land and grass land. Since too many classes will create misclassification and too less classes will lead to approximation [3], these many land cover classes have been identified. These classes are again broadly grouped into two groups: impervious area consisting of building roof tops and asphalt/ concrete and pervious area consisting of swampy/ marshy land, scrub land, agricultural land, grass land, forest and water body. A suitable set of training areas for each class are then selected to carry out the MXL supervised classification. A total of 52 regions were selected for training (impervious-32, pervious-20) amounting to 2.3% of the study area. Here both the J-M distance and Transformed Divergence separability measures are found to be more than 1.9. Thus a good separability is observed between training classes [10] that will lead to an accurate classification. Essentially in order to be acceptable, each class of training data had to have a distinct range [6] of mean values. Hence the statistics were checked to verify its applicability on MXL classification procedure. The evaluation of the training areas suggest that the areas selected would be adequate for the classification process in this study. Hence supervised MXL classification was applied to the image with the above mentioned training areas to obtain the corresponding classified images. The threshold values for all the classes were put zero so that all the pixels will be classified and will come into either pervious category or impervious category.

Misclassification in the study area

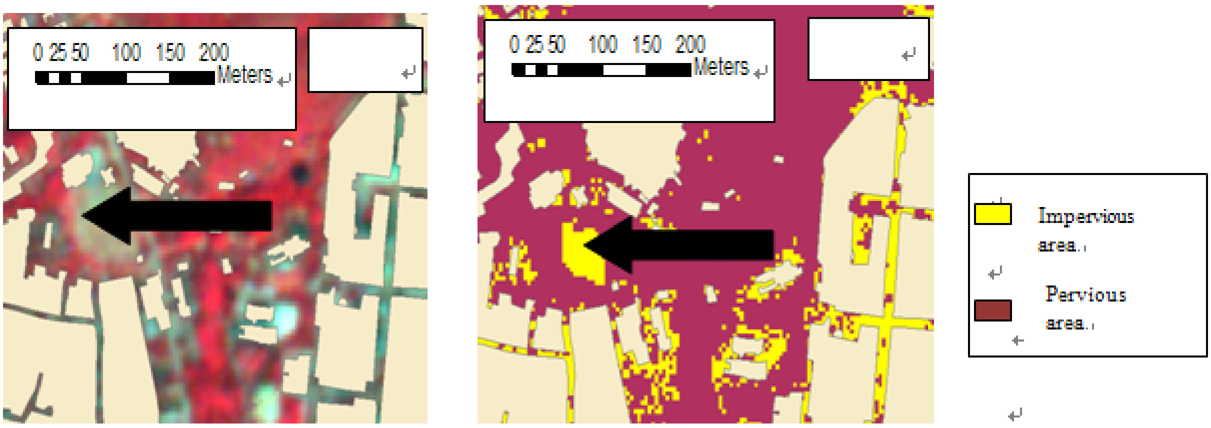
In homogeneous (either urban or rural) areas it is generally possible to get a better land use classification due to the distinct spectral reflectance values between different types of land use. But in peri-urban areas like that of the study area, due to dual influence of rural and urban land covers, it is difficult to find out the land uses as identical reflectance values can correspond to different type of land uses serving different types of functions. Hence the quality of classification is poorer both in terms of the number of individual classes that can be identified and the accuracy with which these classes can be determined. Such an example here is the presence of brick kilns in the study area. In most places one type of soil is found which is red in colour and hence locally known as red soil. Due to the wide availability of the red soil, there are a number of brick kilns found in the study area. Also due to easy availability of this material, residents of this area use roof tiles made up of this red soil. Thus in image analysis, the red roof tiles and the patch of land used as the brick kilns show similar reflectance values due to the red colour and pose difficulty for classification as different type of land use. So if the training area for impervious area is selected from the red roof tiles for classification process, the portion of land which is used as brick kilns (shown in Fig. 2) and should come in pervious category is misclassified as impervious area due to its red colour soil.

On the other side it is also observed that due to leaf cover of tall trees in the road side, other roads and village roads having less width of concrete/ asphalt are mis-classified as vegetation in most of the places of the study area. Hence to avoid such type of misclassification it was decided to use GIS derived data in terms of building footprints and road networks to have greater accuracy. The built-up area estimated from the classification of the imageries includes the building rooftops and the transportation networks. Collectively they are called as Total Impervious Area (TIA).

An effort has been made to obtain a modified classification result over this method of classifying the image with the selected training areas. To have more accurate imperviousness estimation, a set of GIS data is integrated with the satellite image. Thus another classification methodology is applied which uses the GIS data relating to buildings and roads corresponding to the year 2005, collected from Guwahati Metropolitan Development Authority (GMDA). The polygons of buildings and roads were rasterised [4] using the same georeferencing and the same pixel size (5m) as in the satellite classifications and were overlaid earlier classification to get the classifications with GIS data. The imperviousness of all the sub-watersheds estimated by these two methodologies can be used to simulate the runoff.

Result and Analysis

Table 1 shows the imperviousness obtained for different sub-watersheds of the study area. The second column shows the imperviousness in % when the satellite image is classified based on the reflectance values of selected training areas and the third column shows the imperviousness obtained when the GIS data (building footprints and road network) is used in the classification process. It is observed that there is no clear trend of increase or decrease in imperviousness in either method. However the difference in predicted imperviousness in both the methods varies from 0.3% to 23% in different sub-watersheds.



(a) (b)

FIG. 2 BUILDING FOOTPRINTS OVERLAIN ON (a) SATELLITE IMAGE AND (b) CLASSIFIED IMAGE

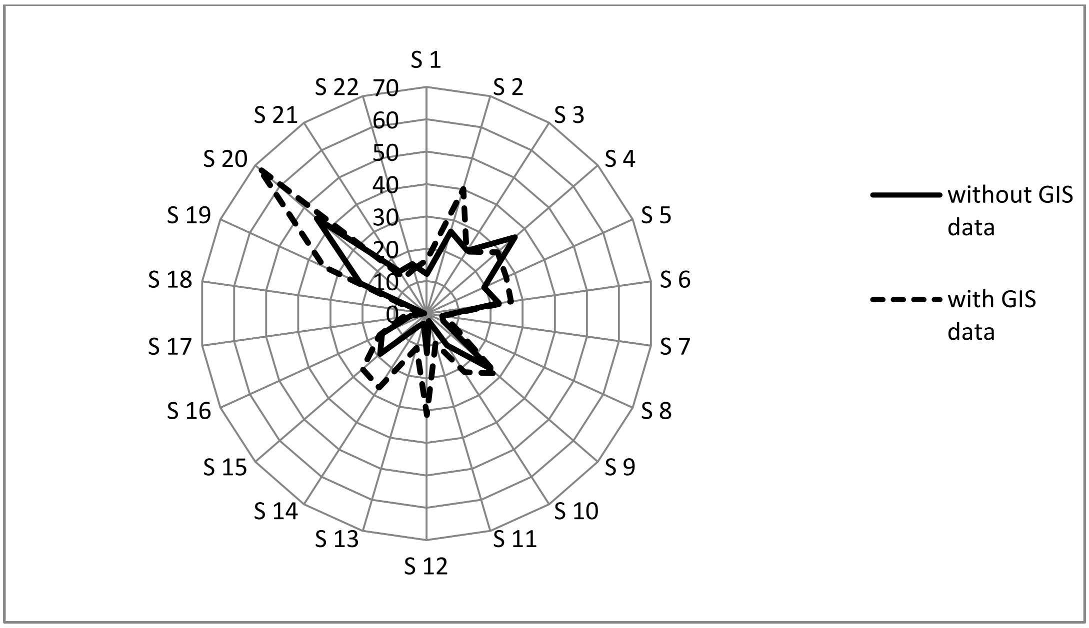


FIG. 2 IMPERVIOUSNESS OF SUB WATERSHEDS OBTAINED WITH AND WITHOUT USE OF GIS DATA

TABLE 1 IMPERVIOUSNESS OBTAINED WITH AND WITHOUT USING GIS DATA

Sub-watershed No.	Imperviousness from only satellite image (%)	Imperviousness by using GIS data (%)
S1	12.24	16.6
S2	26.45	40.125
S3	23.11	22.74
S4	36.0	28.965
S5	19.5	27.03
S6	22.47	26.3
S7	4.86	5.17
S8	5.56	9.13
S9	26.02	28.25
S10	11.68	21.6
S11	2.37	9.633
S12	12.25	31.4
S13	3.21	11.13
S14	4.77	27.17
S15	19.08	26.2
S16	15.12	16.02
S17	5.01	7.4
S18	0.71	2.48
S19	22.5	34.92
S20	44.9	68.48
S21	15.5	13.12
S22	15.9	14.3

The maximum urbanization (68.48%) is detected in sub-watershed 20 (Fig. 2) by both the methods. In most of the sub-watersheds use of GIS data finds the imperviousness more than the use of only remote sensing (satellite image) data. This can be attributed to the fact that the sparsely located hilly settlements in the study area which were not easily captured by the classification algorithm were correctly traced by the use of building foot prints. Hence GIS along with remote sensing data has been found to be an effective tool to find the urbanization and to minimize misclassification in a peri urban area.

Conclusion

Geospatial technologies like remote sensing and GIS has been employed in the current study to determine the imperviousness of a peri urban catchment in North East India. The determined imperviousness by both the methods (with and without using GIS data) varies from 0.3% to 23% in different sub-watersheds of the study area. However their corresponding contribution towards runoff generation is essential in order to access its efficiency for hydrologic modeling and needs further studies. Imperviousness being a primary factor controlling the runoff production needs high degree of accuracy in its determination

process. Since mixed land covers in peri urban areas pose difficulty for image classification, use of a set of GIS derived data will improve the classification process and hence the model output.

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